Error Prone Inference from Response Time:

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Error-prone inference from response time: The case of intuitive generosity in public-good games[☆]

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ABSTRACT

Previous research on public-good games revealed greater contributions by fast decision-makers than by slow decision-makers. Interpreting greater contributions as generosity, this has been seen as evidence of generosity being intuitive. We caution that fast decisions are more prone to error, and that mistakes, rather than preferences, may drive the observed comparative static. Varying the location of the equilibrium in public-good games with a unique dominant strategy, we show that the location of the equilibrium determines whether contributions are larger for fast decision-makers than for slow decision-makers. Replicating previous results, we find that fast decision-makers give more than slow decision-makers when the equilibrium is below the mid-point of the strategy set, but that this result is reversed when the equilibrium is above the mid-point. Consistent with fast decisions being more prone to error, we find that individuals who make (or have to make) fast decisions are insensitive to incentives, more often make mistakes, and are less likely to make equilibrium contributions. These findings make clear that we must control for the rate of errors if we are to draw inference on preferences from response time.

1. Introduction

To better understand the choices people make, researchers have begun to investigate the decision process that leads to choices. Brain imaging, eye tracking, and measures of heart rate and skin conductance have all been used to understand this process.[1] While these physiological measures require special equipment, response time, which is the time it takes individuals to make decisions, is easily acquired and is increasingly used to examine decision-making.[2] For example, response time has been used to predict choices between products, to predict indifference points, to more broadly draw inference on preferences, and to understand strategic thinking and behavior (see Spiliopoulos and Ortmann, 2017 for a review).[3]

Our ability to directly infer preferences from response time, however, hinges on the assumption that observed decisions reflect the underlying preferences, and that the reflection is independent of the time it takes individuals to make a decision. Questioning the validity of this assumption, we find that fast decisions are more prone to error. This holds when response time is endogenously chosen by the decision-maker, and when it is exogenously imposed by the experimenter through time pressure or time delay. Thus, inference on preferences from response time requires that we account for the rate of mistakes.

To demonstrate the potential for false inference from response time we examine the literature on whether individuals are tempted to be generous or to be selfish. This literature extends models on dual selves and dual-processes reasoning to voluntary giving and asks: Is giving

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[1] See e.g., Crawford (2008), Rustichini (2008), Smith and Dickhaut (2005), Caplin and Schotter (2008), Camerer et al. (2005).

[2] The software used in the experimental laboratory automatically records the time it takes for participants to make decisions, thus making it straightforward for scholars to examine how response times correlate with individual choice.

[3] See also Rubinstein (2007, 2013, 2016), Chabris et al. (2009), Milosavljevic et al. (2010), Schotter and Trevino (2012), Agranov et al. (2015), Arad and Rubinstein (2012), and Caplin and Martin (2013).

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impulsive and intuitive or, is it a deliberate and calculated choice?[4] Arguing that intuitive decisions can be inferred from fast decisions and that calculated decisions can be inferred from decisions that are made more slowly, this literature explores how contributions to a public good vary with response time. Lending support to generosity being intuitive, these studies demonstrate in constant-return public-good games (aka voluntary contribution mechanism, VCM) that fast decisions involve greater contributions. This comparative static holds both when response time is endogenously chosen by participants and when it is exogenously imposed by the experimenter through time pressure or time delay.[5]

The concern in using response time to draw inference on preferences is that fast decisions may be more prone to error.[6] This concern is particularly relevant in the VCM, where mistakes cannot be distinguished from generosity (Andreoni, 1995; Houser and Kurzban, 2002), and where fast mistakes can be misinterpreted as fast generosity. In the classic VCM n individuals form a group and each allocates an endowment between a private and a public good. A unit allocation to the private good generates a private payoff of 1, while a unit contribution to the public good secures a payoff of r to each group member, where $1/n < r < 1$. To maximize own material payoffs, it is a dominant strategy to allocate the endowment to the private good, whereas maximization of the group's aggregate material payoff requires that the endowment is allocated to the public good.[7] With the dominant strategy equilibrium of zero contribution to the public good, all equilibrium deviations benefit others and are consistent with generosity. Consequently, quick erroneous deviations from equilibrium will attribute to contributions being greater for fast decision-makers.

To explore the potential role of mistakes, we modify the VCM to a public-good game where mistakes can be identified. We design a game with an interior equilibrium where some deviations from equilibrium decrease both the earnings of the individual and the earnings of other group members.[8] As neither a selfish nor a generous person should be selecting such contributions, we classify them as mistakes and examine whether the rate of mistakes varies with response time. To demonstrate the effect mistakes may have on inference from response time, we look at the effect of varying the location of the equilibrium. The equilibrium in one set of treatments lies below the midpoint of the strategy set (as in the VCM) and in another lies above the midpoint. This variation allows us to explore if the finding that fast decision-makers contribute more than slow decision-makers is robust to changing the location of the equilibrium, and thereby assess whether mistakes may have contributed to the earlier finding.

Our main study uses a 2×3 between-subject design. We examine two different locations of the equilibrium, and three different time treatments. In one of the time treatments, decision-makers freely choose their response time. Time is instead exogenously manipulated in the two other time treatments by imposing a time delay or a time limit.

The two different locations of the equilibrium allow us to assess the relative generosity of fast versus slow decisions, and the role of mistakes when drawing inference from response time. We refer to the treatment with the equilibrium below the midpoint of the strategy set as the "Low" treatment, and to the treatment with the equilibrium above the midpoint of the strategy set as the "High" treatment. If response time solely reflects preferences, then we should find the same generosity ordering of fast and slow decision-makers in the Low and High treatments. In particular, if fast decisions are more generous, then fast decision-makers should make larger contributions in both the Low and the High treatments. In varying the location of the equilibrium we can also assess the responsiveness to incentives and whether it varies with response time.

Our three time treatments help us assess differences in behavior by fast and slow decision-makers. We examine the effect of response time when decision-makers are free to choose how long they take to decide and when they are forced to make a fast or slow decision. In the endogenous-time treatments we classify fast decision-makers as those who use less than the median time to decide. In two exogenous-time treatments we impose either time pressure or time delay. Decisions in time-pressure treatments must be made before the time limit expires and decisions in time-delay treatments cannot be made until after a time limit has passed. In line with the endogenous-time treatments, we refer to participants in the time-pressure treatment as fast decision-makers and to those in the time-delay treatment as slow decision-makers.

Our results from the Low endogenous-time treatment replicate existing research on intuitive generosity, showing that fast decision-makers contribute more than slow decision-makers. However, this relationship is reversed in the High endogenous-time treatment, where fast decision-makers contribute less than slow decision-makers. We find in both the Low and High endogenous-time treatments that fast decision-makers are more likely to make mistakes. That is, they choose contributions that simultaneously decrease earnings to themselves and to other group members. By contrast, slow decision-makers are more likely to contribute the equilibrium amount, and when they deviate from the dominant strategy they are more likely to make welfare-improving contributions. Comparing the Low and High treatments we find significant differences in the contributions made by slow decision-makers, while those made by fast decision-makers are not distinguishable by treatment. These results are replicated in the treatments with exogenous time-pressure and time-delay. Thus, fast decision-makers appear insensitive to incentives and are more prone to error, irrespective of whether they voluntarily make fast decisions or are forced to do so.

All these findings are from one-shot interactions. We also have data from repeated interactions, which shows that contributions quickly converge toward the interior equilibrium. Convergence of average contributions occurs from above in the Low treatments and from below in the High treatments. These opposing directions of convergence are consistent with overcontribution in the Low treatment and the undercontribution in the High treatment being due to mistakes.

As noted above, our main study examines contributions in a public-good game with an interior equilibrium. Specifically, we rely on piecewise linear payoff functions that allow us to identify mistakes. The resulting payoff structure is less transparent than that of the classic VCM games, and this complexity may increase the rate of mistakes

[4] Central to models of dual selves is that decisions are influenced by an intuitive system which is responsible for automated, rule-based choices, and by a deliberative system, through which calculated reflective decisions are made (see e.g., Evans, 2008; Kahneman, 2003, 2011; Shefrin and Thaler, 1988; Loewenstein and O'Donoghue, 2004; Benhabib and Bisin, 2005; Bernheim and Rangel, 2004; Fudenberg and Levine, 2006, 2012). Examples of studies asking whether generosity is intuitive or calculated are Martinsson, Myrseth, and Wollbrant (2012), Kocher et al. (2017), Kinnunen and Windmann (2013), Kessler and Meier (2014), Achtziger et al. (2015), Yamagishi et al. (2017). Dreber et al. (2016) extends the dual-self model to account for intuitive generosity. While it is important to understand whether generosity is intuitive, it is less clear how one is to examine it. For example, Vesterlund (2016) argues that a temptation to give generates the same comparative statics as those attributed to "avoiding the ask" in DellaVigna et al. (2012). Some studies suggest that generosity is intuitive while others find evidence in favor of a deliberate generosity hypothesis. For example, Ruff et al. (2013), and Kinnunen and Windmann (2013) show evidence consistent with other-regarding behavior being intuitive, while Achtziger et al. (2015, 2016), Knoch et al. (2006), Kocher et al. (2017), Fiedler et al. (2013) and Strang et al. (2014) show evidence consistent with other-regarding behavior being a deliberative choice.

[5] See Rand et al. (2012), Lotito et al. (2013) and Nielsen et al. (2014) for studies examining the correlation between contributions and response times. Tinghög et al. (2013), Rand et al. (2014), and Bouwmeester et al. (2017) examine the response to time pressure.

[6] Studies examining the correlation between response times and choices in beauty contest games show that lower frequencies of dominated choices are associated with larger response times (e.g., Kocher and Sutter, 2006; Rubinstein, 2007; and Agranov et al., 2015).

[7] Throughout the paper we use the term 'dominant strategy' to refer to selfish material payoff-maximizing choices, and Nash equilibrium refers to the Nash equilibrium under narrow material selfishness.

[8] We maintain an equilibrium in dominant strategies and place both the equilibrium and the group-payoff-maximizing outcomes away from the boundaries and the midpoint of the strategy set. These non-linear public-good games allow us to identify mistakes and to better capture the incentives associated with voluntary contributions to public goods. Examining voluntary contributions to public goods, be it in theoretical or empirical work, researchers assume that there exists an interior equilibrium where individuals have a private incentive to secure the good (street lighting, clean air, etc.) and where the marginal return from such goods are decreasing (e.g., Bergstrom et al., 1986).

(although such an increase should not affect whether mistakes are more likely to be made by fast or slow decision-makers). We therefore conduct an additional set of experiments where we ask whether similar results arise when the return to giving is constant as in the VCM, but the strategy set includes contributions that are dominated from an individual and group perspective. By adding a private benefit for contributing to the public good, we examine how contributions change when we move the dominant strategy from one of zero contribution to one of full contribution. In the latter case, any contribution below full contribution reduces the earnings of the individual and of all other group members. This High-VCM treatment replicates our results. In contrast to previous (Low-) VCM results, we find that fast decision-makers contribute less than slow decision-makers. As with our interior-equilibrium designs, we also examine how sensitive decisions are to the location of the equilibrium by comparing contributions in the Low-VCM and High-VCM treatments. Consistent with our results in the interior equilibrium experiments, fast choices appear to be insensitive to treatment changes while slow choices vary significantly by treatment.

Examining choices of 476 participants in different variations of our Low and High treatments, we find that choices by slow decision-makers respond to incentives and are sensitive to the location of the equilibrium, while choices made by fast decision-makers are indistinguishable by the respective Low and High treatments. This insensitivity to treatment is particularly intriguing considering the range of dominated actions is much greater in the High than Low treatments. The lack of response to treatment by fast decision-makers indicates that fast choices are unlikely to reflect (solely) preferences over payoffs. Thus, for fast decisions one must be careful in interpreting deviations from equilibrium as evidence of (non-) standard preferences. As in the work on rational inattention and costly information processing by Caplin and Dean (2015) it may be that dominated choices (by fast decision-makers) result from an unwillingness to trade cognitive effort for monetary reward in our endogenous-time treatments, and an inability to do so in our exogenous-time treatments.

In addition to examining the ability to directly infer preferences from response time, our study makes three broader methodological contributions. First, in identifying mistakes we demonstrate that a number of participants fail to internalize the incentives presented to them in the experiment. This resonates with the "failure of game-form recognition" documented by Cason and Plott (2014). Failure to internalize incentives must be considered not only when examining response time, but in any study where confusion or lack of attention and motivation leads to mistakes that may influence inference. Second, and intriguingly, it appears that response time is one way in which we may be able to evaluate the effect of mistakes. Third, our study serves as a demonstration of what is needed for causal inference. Studies of high internal validity eliminate confounding factors, thus securing that inference comes not only from confirmation of a predicted comparative static, but also from elimination of alternatives that generate the same comparative static.

2. Related literature

The economics literature is increasingly relying on measures of response time to study decision-making. Early work by Wilcox (1993) viewed response time as a proxy for decision cost and analyzed choices in risky environments. The subsequent literature has used response time to investigate the decision process employed by individuals, to make inferences about preferences, and to predict choices within and across domains (see Spiliopoulos and Ortmann, 2017 for a review).[9]

Rubinstein (2007) put forward the idea that fast choices are instinctive while slow choices are cognitive and analyzed the correlation between response times and choices in seven different strategic environments (see also Kahneman, 2011). Together with Rubinstein (2013, 2016) the work documents large variation in the types of choices associated with fast response times.[10] Rubinstein (2016) develops a typology of players that uses response times and the choices associated with slow response times to study and predict decision-making across games.

The literature has used two different response-time methods to identify intuitive and deliberate actions in public-good games. One method examines how an individual's self-chosen response time correlates with contributions. Using this method, Rand et al. (2012) find a negative correlation between contributions and response time in the standard VCM, and see this as consistent with generosity on average being an intuitive response and greed on average being a calculated response. Lotito et al. (2013) replicate this results when endowments are asymmetric, and Nielsen et al. (2014) do so when instead a strategy method is employed.[11]

A potential concern in examining endogenously arising response time, however, is that the inference may result from selection into fast and slow decision-making based on the strength of preferences (reverse inference). In particular, very generous participants may respond quickly not because they are intuitively generous but rather because the decision is an easier one for them to make (Krajbich et al., 2015). As very selfish participants also may find the decision easier, the argument is that the negative correlation between response times and contributions may result if the share of these very generous participants exceeds that of the very selfish participants. To control for this, a second response-time method manipulates response time by giving participants a time limit to either induce time pressure or time delay. In examining the effect of time pressure, Rand et al. (2012, 2014) find that individuals who have to make quick decisions are more generous than those who have to take time to decide. Tinghög et al. (2013) and Bouwmeester et al. (2017) largely fail to replicate this result and note a potentially different selection problem that may result when participants fail to obey the time limit.

The literature on public-good contributions, or generosity more broadly defined, and response time has to date given limited attention to the role of error. Specifically, it has not examined choices in environments that can identify both generosity and mistakes. As noted above, mistakes are of particular concern in the VCM where all deviations from the equilibrium are welfare improving and thus can be rationalized by generosity.[12] If errors are independent of response times

[9] We limit our review to research related to intuitive actions, generosity, and error. Research on response times and decision-making in other environments include Chabris et al. (2009); Milosavljevic et al. (2010); Krajbich et al. (2010); Krajbich and Rangel (2011); Krajbich et al. (2012); Clithero and Rangel (2013); Krajbich et al. (2014); and Schotter and Trevino (2012). Examples of exogenous manipulations of response time is seen in Ibanez et al. (2009), Cappelletti et al. (2011); Nursimulu and Bossaerts (2014); Kocher et al. (2013), and Reutskaja et al. (2011).

[10] In Rubinstein (2007, 2016) fast decisions are associated with fair outcomes in some settings, with equilibrium and efficiency maximizing choices in others, and with the use of strictly dominated choices in yet other environments. In many of the strategic settings investigated, focal choices coincide with fair, equilibrium, efficiency maximizing, and strictly dominated strategies.

[11] Branas-Garza et al. (2016) document a negative correlation between offers to responders and proposers' response times in the ultimatum game. Rubinstein (2007, 2016) shows only a negative correlation when offers above the 50–50 threshold are excluded. Analysis of non-strategic environments such as the dictator game and actual donation decisions shows mixed results. Piovesan and Wengström (2009) find a positive correlation between offers in the dictator game and response time. Cappelen et al. (2016) show instead that equal split offers are associated with faster response times than selfish choices in the dictator game. Lohse et al. (2016) show that response times are positively correlated with monetary contributions to CO_2 emission. Kessler et al. (2017) examine dictator and prisoners' dilemma games varying the return to altruistic actions following the procedure of Caplin et al. (2011) and Agranov et al. (2015) to incentivize participants to make a choice during every second of deliberation, and find that fast decisions are not always associated with selfishness or generosity but rather that efficiency concerns matter.

[12] Similarly, deviations from the (subgame perfect) Nash equilibrium in the standard dictator game and in the ultimatum game can also be seen as generous behavior (for alternative views see Cherry et al., 2002, Bekkers, 2007, and Dana et al., 2007). While it is tempting to argue that offers in excess of 50% of the endowment are mistakes in these settings, response time data indicates that such generous choices are sometimes associated with slow response times and thus seen as indicative of deliberation (see e.g., Rubinstein, 2007, 2016; and Piovesan and Wengström, 2009). Furthermore, in such settings the midpoint of the strategy set is focal and coincides with the fair outcome, making it impossible to distinguish between focal, generous or fair choices, and mistakes.

this is, of course, not an issue for inference on preferences. However, it becomes an important confound if errors are systematically related to the time individuals take (or are forced to take) to decide. If it holds that fast (or slow) decision-makers more frequently make mistakes, then response time will be a poor measure of preferences.[13]

The aim of our study is to demonstrate that mistakes can be systematically related to response time and that failure to account for mistakes may cause the inference of intuitive responses to reverse across strategic environments. Our study contributes to the literature by asking whether response time is a reliable indicator of individual preferences in public-good games. Specifically, we examine contributions in a strategic setting where we can distinguish quick mistakes from intuitively generous behavior and examine whether error affects the comparative static on the relative generosity by fast and slow decision-makers.[14] While our study focuses on public-good games, our results are also informative on inference from response time in other settings. Mistakes are likely to play a prominent role in many strategic environments, hence inference on preferences from such settings require that mistakes and their distribution over time are accounted for.

3. Identifying mistakes

In the standard VCM it is not possible to determine whether individuals, in making a positive contribution, are making a mistake or aiming to increase the earnings of others. Impeding the identification of mistakes is that any deviation from the dominant strategy of zero contribution increases group payoffs. We design a set of public-good games where mistakes can be identified. This allows us to examine whether preferences can be inferred from response time. More specifically, we examine two different types of public-good games. One with an interior equilibrium and one where the equilibrium is at the boundary.

The first type uses piecewise linear payoffs to secure a unique interior Nash equilibrium in dominant strategies and an interior group-payoff-maximizing contribution. This type of public-good game secures that there are deviations from equilibrium that decrease both the earnings of the individual and the earnings of other group members. Such decisions are unambiguously dominated for individuals aiming to increase the earnings to self and/or others, and can thus be classified as mistakes.[15] The existence of these dominated decisions allows us to examine how the rate of mistakes varies with response time. We examine two different treatments. In one treatment (Low) the interior equilibrium lies below the midpoint of the strategy set (as in the VCM), and in the other treatment (High) it lies above the midpoint. Thus, the range of contributions that constitute mistakes is larger in the High treatment than in the Low treatment. Comparing the two treatments we can thus assess the sensitivity to incentives and whether it varies with response time. Moreover, we can determine the robustness of the earlier finding that fast decision-makers contribute more than slow decision-makers. If fast decisions are more prone to error, then we may find a reversal of the earlier finding when moving from an equilibrium below the midpoint of the strategy set to an equilibrium above it. Such a reversal would be inconsistent with greater fast contributions solely reflecting preferences.

The second type of public-good games uses linear payoffs (as in the VCM) maintaining that full contribution maximizes group-payoffs and placing the dominant strategy equilibrium at the boundary of the strategy set. The dominant-strategy equilibrium in one treatment (Low-VCM) is at zero contribution, while an added private contribution benefit places the equilibrium at full contribution in the second treatment (High-VCM). Even though mistakes cannot be identified in the Low-VCM, they can be identified in the High-VCM, where full contribution is dominant both from an other-regarding perspective and from a selfish individual payoff-maximizing perspective. As in the interior equilibrium treatments, we can also identify how fast and slow decision-makers respond to changes in incentives by comparing their contribution decisions in the Low-VCM and the High-VCM treatments.

In what follows, we first describe the design and results of our first set of public-good treatments. We report on the interior public-good game treatments along with several robustness checks (Section 4). We then proceed to report on the Low- and High-VCM treatments where the equilibria are at the boundary of the strategy set (Section 5).

4. Public-good games with interior equilibria

We first describe the payoff structure of the interior public-good games followed by the procedures and results of the experiment.

4.1. Payoffs

To secure an interior equilibrium we use a piecewise linear payoff structure similar to that of Bracha et al. (2011).[16] Participants are matched in groups of four and each is given a $10 endowment and asked how much they wish to contribute (in $1 increments) to a group account. Contributions to the group account generate a constant and equal benefit to the other group members (as in the VCM). An interior dominant strategy equilibrium is secured by modifying the individual's private benefit of contributing such that it is approximately concave (using a piecewise linear approximation).

We construct piecewise linear payoffs with the following five characteristics. First, there is an interior Nash equilibrium in dominant strategies, which varies by treatment. In the Low treatment, the equilibrium contribution is $3 and in the High treatment the equilibrium contribution is $7. Second, there is a unique interior group-payoff-maximizing contribution of $9, which is the same in both treatments. Third, equilibrium payoffs as well as the boundary payoffs associated with contributing $0 and $10 are held constant across treatments. Fourth, payoffs are chosen such that individually costly but group-payoff-improving contributions range from $4 to $9 in the Low treatment, and from $8 to $9 in the High treatment, while the individual's cost of deviating from the equilibrium contribution toward the middle of the strategy set (between $3 and $7) is held constant in the two treatments. Fifth, there are deviations from equilibrium that can be classified as mistakes because they simultaneously decrease the payoffs of the decision-maker and of all other group members. These contributions range from 0 to 2 in the Low treatment and from 0 to 6 in the

[13] Evidence on how mistakes vary with response time is mixed. Rubinstein (2013) finds in 10 decision tasks that mistakes decrease with time when facing questions that have a definitive right answer, mistakes defined as violations of transitivity instead increase with time, and mistakes defined as violations of consistency do not change with time. Time pressure has been shown to increase the rates of rejection in the first round of a repeated ultimatum game (Sutter et al., 2003) and to increase guesses in the beauty contest game (Kocher and Sutter, 2006). Rubinstein (2007) shows that choices at or above the midpoint of the strategy set in the 2/3 beauty contest game are associated with faster response times. Agranov et al. (2015) use a strategy-type method that maps choices over response time in the beauty contest game and show that while the guesses of strategic players decrease with response time, non-strategic players make average guesses that coincide with the midpoint of the strategy set and do not change with time. Gill and Prowse (2017) show in a between-subject analysis of repeated decisions in the beauty contest game that higher response times are associated with lower guesses, higher success rates, and higher earnings.

[14] A potential reversal of the comparative static on relative generosity between the High and Low treatments addresses the concern of reverse inference driving the comparative static in treatments where participants endogenously select their response time. If particularly generous (or particularly selfish) individuals make faster decisions than those with less intense preferences, then we would expect a similar comparative static in the High and Low treatments.

[15] Our objective is to identify potential mistakes and not the mechanism behind them, which could be inattention, confusion, lack of motivation and more. The identification of these mechanisms is beyond the scope of this paper and we leave it for future research.

[16] This piecewise linear payoff structure has also been used by others. E.g., Menietti et al. (2012), Menietti (2012), Cason and Gangadharan (2015), and Robbett (2016).

Table 1
Design features.

Treatment	Low	High
Endowment	10	10
Dominant strategy	3	7
Group-payoff-maximizing contribution	9	9
Mistakes	0–2	0–6

High treatment. Table 1 summarizes the features of the design. The precise payoff function and payoff tables are shown in the Appendix A.

Our design allows us to assess whether fast- or slow-deciding participants make more mistakes and whether fast decision-makers contribute more, independent of treatment. If mistakes are more frequently made by fast decision-makers, we may find that fast decision-makers contribute more than slow decision-makers in the Low treatment and find the reverse relationship in the High treatment. The sensitivity to treatment is intriguing as the range of contributions that classify as mistakes is far greater in the High than in the Low treatment.

4.2. Experimental procedures

Here we describe the procedures of the endogenous-time treatments. That is, the treatments where each participant could make a choice at his or her own pace. Procedures of the time-pressure and time-delay treatments, where participants were respectively forced to make decisions within some time limit or had to wait for some time before being allowed to submit a decision, are similar. Differences are explained when introducing these treatments in Section 4.4.2 and in the online Appendix.

The experiment was conducted at the Pittsburgh Experimental Economics Laboratory (PEEL) at the University of Pittsburgh. Using a between-subject design we conducted four sessions of each of the two treatments. With 20 participants per session a total of 160 undergraduate students participated in these treatments. Each session lasted approximately 45 min with average payments being $22.50 per subject (including a $6 show up fee).

Upon entering the lab, participants were seated in a pre-marked cubicle, and were asked to provide informed consent to participate in the study. We then distributed instructions and read them out loud. Participants were informed that they would be matched in groups of four and that they would each be given an endowment of $10, which they could invest in $1 increments in a group account. Participants knew that investment decisions would affect their payoffs and the payoffs of other group members, but were given no details on the actual payoff structure. They were told that this information would be presented via payoff tables displayed on the computer screen. The instructions explained how they should read the payoff table and informed them that they would have to complete a tutorial before proceeding.[17]

Interfaces for the tutorial and for the decision-making part of the experiment were programmed using z-Tree (Fischbacher, 2007). The tutorial used an abstract payoff table in which participants had two investment options. The payoffs in each cell were denoted using matrix notation. That is, no monetary payoffs were presented but rather combinations of letters and numbers (e.g., $A11). This procedure allowed participants to learn how to read the payoff table without the possibility of deliberating about selfish and/or generous choices. Thereafter, participants had to answer six tutorial questions, which asked them to identify the abstract payoffs associated with different investment choices made by all group members. The tutorial allowed participants to enter incorrect answers, but presented solutions to ensure comprehension.

The decision-making phase began after the tutorial. Individual computer screens displayed the payoff table and asked participants to make a contribution decision. For a given contribution made by the other three group members, the payoff table listed, for each possible contribution decision between $0 and $10, the individual's payoff and the average payoffs of the other group members. Time was recorded as the number of seconds it took participants to make a decision after seeing the payoff table. Time was not displayed on the decision screen. Once all contributions were made participants were shown a payoff screen informing them of their own contribution, the total and average contribution of other group members, their own payoff and the average payoff of the other group members.

This ended Part 1 of the experiment and participants received instructions for Part 2. No details on Part 2 were given prior to this stage. Part 2 consisted of 10 periods of the same decision scenario as Part 1. Participants were informed that in each period they would be randomly re-matched with other group members, and that they could not be rematched with the same group members twice in a row. Participants were at the beginning of the session informed that the experiment would consist of two parts and that only one of the two parts would count for payment. If Part 2 was selected for payment, only one randomly selected period would be paid. At the end of each period participants received the same feedback as in Part 1. After completing the decision phase participants received a demographic questionnaire to determine age, gender, nationality, year in college, and college major.

4.3. Results

In this section we use Part 1 decisions to assess the relationship between endogenously chosen response times and contributions. We start with a description of contributions, then report on the correlation between contributions and response time, and finally examine how choices by fast and slow decision-makers differ. In Section 4.4 we examine the robustness of our results by reporting on three different sets of data, including the Part-2 data and data from the treatments with time pressure and time delay.

4.3.1. Contributions

Our first result is that generally participants respond to the different incentives in the Low and High treatment. Fig. 1 presents a histogram of contributions by treatment. It shows that the modal contribution in the Low and High treatment is the equilibrium prediction ($3 and $7, respectively); 35% of participants in the Low treatment contribute $3 and 36% of participants in the High treatment contribute $7.[18]

In the Low treatment the average contribution exceeds the equilibrium prediction of $3 (mean = $5.06, $p < 0.01$), whereas in the High treatment it falls short of the equilibrium prediction of $7 (mean = $6.57, $p < 0.10$).[19] Hence, relative to the equilibrium prediction, participants overcontribute in the Low treatment and undercontribute in the High treatment, and contributions in the Low treatment are below those in the High treatment ($p < 0.01$).[20]

In both the Low and High treatments we see deviations from equilibrium that decrease both individual and group payoffs. These payoff-reducing contributions include contributions below the equilibrium and above the group-payoff-maximizing contribution of $9. While contributions below the dominant strategy can clearly be interpreted as

[17] The payoff tables used in the experiment are presented in the paper Appendix. For the instructions see the online Appendix.

[18] This frequency of equilibrium play is higher than that usually documented for VCMs. Isaac et al. (1984) document a 30% frequency of equilibrium play (across 10 rounds) in VCMs with varying group sizes and marginal per capita returns (19% in the first round of play when group size is four). See Ledyard (1995) and Chaudhuri (2011) for a review of frequency of equilibrium play in VCM studies.

[19] Unless otherwise noted all tests are two-sided *t*-tests.

[20] The differences in the distribution of contributions across treatments are statistically significant (Kolmogorov-Smirnov $p < 0.01$).

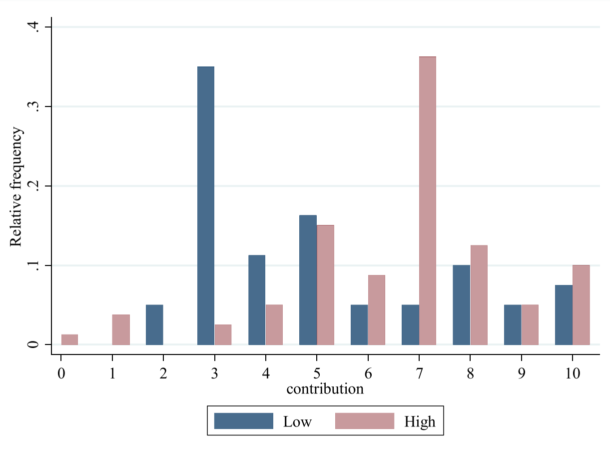

Fig. 1. Histogram of contributions by treatment, Part 1
Note: The equilibrium contribution is 3 in the Low treatment and 7 in the High treatment. The group-payoff-maximizing contribution is 9 in both treatments.

Table 2
OLS regression of contributions on response time.

Dep. Var.: contribution to group account	Low (1)	High (2)	All (3)
Response time	−0.019**	0.016**	−0.019***
	(0.008)	(0.006)	(0.007)
High			−0.205
			(0.598)
High x response time			0.035***
			(0.010)
Constant	6.024***	5.819***	6.024***
	(0.469)	(0.376)	(0.443)
N	80	80	160

Note: Standard errors in parentheses.
** $p < 0.05$.
*** $p < 0.01$.

mistakes, because they simultaneously decrease the contributions of the decision-maker and of all other group members, contributions in excess of \$9 could be either mistakes or a sign of extreme generosity. The individual costs associated with giving \$10 rather than \$9 are so large that they exceed the increase in total earnings of other group members and thus decrease overall group payoffs. However, such contributions cannot be identified as mistakes as they may result from a very high level of generosity. In Section 4.4 we report on additional experiments with a slightly modified payoff structure where contributions of \$10 decrease earnings for both self and others, allowing us to classify \$10 contributions as mistakes.

Interestingly, when disregarding equilibrium play, the distributions of contributions in Fig. 1 appear insensitive to treatment. Absent contributions of \$3 and \$7 we cannot reject the null hypothesis that the two samples come from the same underlying distribution (Kolmogorov-Smirnov $p = 0.780$), nor can we reject that the average of the contributions are the same (mean Low = \$6.10, mean High = \$6.47; $p = 0.479$). The similarity in contributions is particularly striking when considering contributions of \$4, \$5, and \$6. While these contributions may be seen as generous in the Low treatment, they are dominated from a group and individual perspective in the High treatment.[21] The similarity of these non-equilibrium contributions across treatments with vastly different incentive structures, suggests that costly welfare-improving contributions in the Low treatment are not reflective of generous contributions but rather of mistakes.

4.3.2. Response times and contributions

The time it takes to make a contribution decision varies substantially across participants. Some participants spend as little as 4 s making a decision whereas others spend several minutes deciding. However, response times do not differ by treatment.[22]

Using OLS regressions with contributions as the dependent variable we explore the correlation between response times and contributions.[23] Column 1 of Table 2 shows the results for participants in the Low treatment. The negative and statistically significant coefficient on response time reveals that fast decision-makers contribute more than slow decision-makers when the equilibrium is below the midpoint of the strategy set, thus confirming earlier VCM findings. The estimated coefficients correspond to participants who delay their decision by 1 min on average contributing \$1.14 less than those who make a contribution decision right away.

The correlation between contributions and response times is, however, sensitive to treatment. Column 2 of Table 2 shows that in the High treatment the correlation is reversed. The positive and significant coefficient reveals that fast decision-makers contribute less than slow decision-makers. The coefficient on response time is of similar absolute magnitude as the one estimated in the Low treatment. A participant who delays the decision by 1 min on average contributes \$0.96 more than someone who makes a contribution right away. Column 3 of Table 2 pools the data from the two treatments to test whether treatment effects are statistically different. Using a difference-in-difference regression of contributions on response time and treatment, the regression result shows two things. First, the insignificant coefficient of the dummy variable High (1 if treatment is High, 0 otherwise) reveals that when controlling for response time there is no difference in contributions between treatments. Second, the positive and statistically significant coefficient of the interaction between the dummy High and response time (High × response time) shows that the correlation between contributions and response times differs between treatments. While for fast decision-makers there is little difference in contributions between the Low and High treatments, the difference increases with response time, implying that the treatment differences seen in Fig. 1 result from slow decisions.[24]

The treatment insensitivity of fast decision-makers is summarized in Fig. 2. Following the literature (e.g., Rand et al., 2012; Rubinstein, 2013, 2016), we use the median response time of the pooled sample (41.5 s) to define fast and slow decision-makers.[25] Fig. 2 shows that while there are no significant treatment differences in the average contributions by fast decision-makers (Mean Low = \$5.54, Mean

[21] The similarity in frequency of \$10 contributions is noteworthy given the substantial treatment differences in the cost of contributing \$10.

[22] Response time in seconds: Mean Low = 50.6, Mean High = 46.78, $p = 0.497$; Median Low = 41, Median High = 42.5; Wilcoxon Mann-Whitney rank-sum test $p = 0.452$; Kolmogorov-Smirnov $p = 0.560$. Online Appendix Figure C1 shows the cumulative distribution function of response time by treatment.

[23] Online Appendix Table C1 presents Tobit regressions that account for censoring at \$0 and \$10 and provide similar results.

[24] In online Appendix Table C2 we show that the correlations between response times and contributions documented in Table 2 are robust to controlling for age, gender, the number of tutorial questions answered correctly, training in economics, and experience with laboratory experiments. The results are also robust to excluding outlier observations. Specifically, eliminating observations with response times in excess of 150 s does not alter the coefficients on response time reported in Table 2 irrespective of including the full set of controls in the regressions. See online Appendix Table C3.

[25] Results are similar if an alternative definition of fast and slow decision-makers is used which cuts the data at the fastest quartile of the distribution. The alternative definition shows insensitivity to payoffs among fast but not slow decision-makers and a positive correlation between response time and contributions in the High treatment. The correlation between response time and contributions is negative but small and statistically insignificant in the Low treatment. Results are available from the authors upon request.

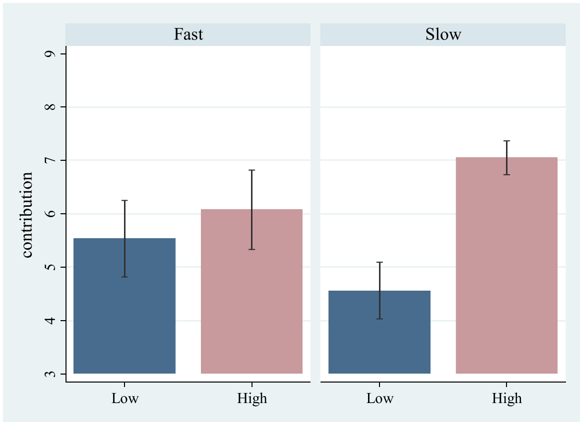

Fig. 2. Mean contribution by fast and slow decision-makers, Part 1
Note: Fast indicates that choices were made in less than the median response time, and slow indicates that choices were made in the median response time or more.

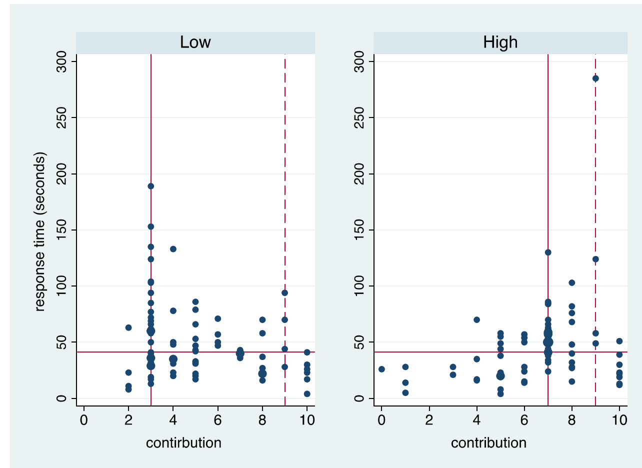

Fig. 3. Scatterplot of contributions and response time by treatment, Part 1
Note: The solid vertical line indicates the Nash contribution, the dashed vertical line indicates the group-payoff-maximizing contribution, and the solid horizontal line indicates the median response time of the pooled sample (41.5 s).

High = \$6.08, $p = 0.380$), there are substantial and statistically significant differences in the average contributions by slow decision-makers (Mean Low = \$4.56, Mean High = \$7.05, $p < 0.01$). Consistent with Table 2 we find in the Low treatment that fast decision-makers contribute more than slow decision-makers, but that the reverse holds true in the High treatment ($p = 0.072$ and 0.042 in each treatment respectively). We also note that in both treatments standard deviations are smaller for slow decision-makers.[26]

The results reported in Table 2 and Fig. 2 illustrate the difficulty associated with drawing inference from response time. The location of the equilibrium determines whether fast decision-makers contribute more than slow decision-makers or vice versa. Looking at the distribution of contributions by response time it becomes clear why the comparative static reverses with treatment. Fig. 3 presents a scatterplot of response times and contributions by treatment. The solid vertical line indicates the location of the equilibrium contribution (\$3 and \$7 in the Low and High treatment, respectively) and the dashed vertical line indicates the location of the contribution that maximizes the group's total earnings (\$9 in both treatments). The horizontal line indicates the median response time of the pooled sample, separating fast decision-makers below the horizontal line, from slow decision-makers above the horizontal line. Inspecting the segments below the median response time in the two panels of Fig. 3, we see that despite the vastly different incentives fast contributions are similarly distributed in both treatments. In contrast, slow contributions, depicted in the segments of Fig. 3 above the median response time, show clear treatment differences.[27]

Table 3 summarizes the information contained in Fig. 3 and reports the percentage of choices that are attributed to fast response times in each treatment. Mistakes are defined as contributions that simultaneously decrease the payoff to the individual and to all other group members. That is, contributions that fall below \$3 in the Low treatment and below \$7 in the High treatment. The first row in Table 3 shows that mistakes are overwhelmingly associated with fast response times in both treatments. With 72% of mistakes being made in less than the median response time we reject the null hypothesis that slow and fast decision-makers are equally likely to make mistakes (2-sided Fisher's exact test $p < 0.01$ in the pooled sample).[28] Moreover, contributions of \$10, which are dominated from a group-payoff-maximizing perspective, are also associated with fast responses (2-sided Fisher's exact test $p < 0.01$ in the pooled sample). By contrast, both equilibrium and group-payoff-maximizing contributions are more likely to be made by slow decision-makers (2-sided Fisher's exact test $p < 0.01$ and $p = 0.064$, respectively, for equilibrium and group-payoff-maximizing contributions in the pooled sample).[29]

Table 3
Contributions by treatment.

	Low		High		All	
	# obs.	% fast	# obs.	% fast	# obs.	% fast
Mistakes (below Nash)	4	75	29	72	33	73
Nash equilibrium	28	39	29	21	57	30
Above Nash & below group-payoff-max.	38	53	10	50	48	52
Group-payoff-maximizing	4	25	4	0	8	13
Full provision (reducing group payoff)	6	100	8	88	14	93
Midpoint of strategy set	13	46	12	67	25	56
All	80	51	80	49	160	50

Note: "fast" indicates that contribution decisions were made in less than the median response time.

Overall, our results show that the comparative statics of relative generosity by fast versus slow decision-makers is sensitive to the location of the equilibrium. While fast decision-makers do not generally contribute more than slow decision-makers, they are more likely to select a contribution that simultaneously lowers individual and group payoffs, and their average contribution is unaffected by the treatment.

[26] Tests for differences in the standard deviation of contributions reject the null hypothesis that the variance of the contributions is the same for fast and slow decision-makers (Brown - Forsythe robust test $p < 0.05$ in both treatments).

[27] For fast decision-makers, the distributions of contributions do not differ significantly by treatment (Wilcoxon Mann-Whitney rank-sum test yields $p = 0.232$, and Kolmogorov-Smirnov $p = 0.229$), whereas those for slow decision-makers do ($p < 0.01$ for both Wilcoxon Mann-Whitney rank-sum and Kolmogorov-Smirnov tests).

[28] Using response times rather than the fast versus slow partition to analyze whether mistakes are associated with fast response times yields similar results. A probit regression of mistakes on response time and treatment returns statistically significant marginal effects at means on response time in the pooled sample (coeff: −0.00494; s.e. = 0.001, $p < 0.001$). Results are also significant when analyzing the correlation between mistakes and response time separately by treatment.

[29] We report pooled data statistics because by treatment the number of observations in some bins is very small. The 2-sided Fisher's exact test statistics for the Low and High treatment separately are for mistakes (Low: $p = 0.616$; High: $p < 0.01$), equilibrium contributions (Low: $p = 0.160$; High: $p < 0.01$), group-payoff-maximizing contributions (Low: $p = 0.353$; High: $p = 0.116$) and contributions of \$10 ($p < 0.05$ in both treatments).

Rather than fast decision-makers being more generous, our results indicate that fast decision-makers are more prone to making mistakes than slow decision-makers.

4.4. Robustness checks: modified interior public-good games, time pressure and time delay, dynamics of contributions

To further examine the role of mistakes we analyze three additional sets of data. First, we conduct a set of additional experiments where we slightly alter the payoff function to secure that contributing the whole endowment decreases both the payoffs of the individual and of the other group members, and thus can unambiguously be interpreted as a mistake. Using this modified design, we ask whether the frequency of full contributions responds to this change in incentives and whether we replicate our initial results. Second, we examine whether our results from the reported experiments with endogenously chosen response times are robust to exogenously imposing time limits. That is, we examine behavior when decisions are made under time pressure or with time delay. Finally, across the different types of treatments we examine how contributions change and potentially converge in Part 2 of the experiment.

4.4.1. Is contributing the whole endowment a mistake? Mod-low and mod-high treatments

The analysis above revealed that contributions of $10 were predominantly made by fast decision-makers. Although such contributions decrease individual as well as overall group earnings, they can be rationalized assuming extremely generous preferences.[30] We therefore conduct additional treatments where an increase in contributions from $9 to $10 lowers earnings both for the individual and for every other member of the group.[31] Keeping the payoffs of all other combinations of contributions the same as in the initial interior equilibrium experiments, this ensures that both the lower and upper boundary of the strategy set are dominated from the perspective of the individual and of the other group members. We conduct four sessions of these treatments, two with the Modified-Low treatment and two with the Modified-High treatment. With 40 participants in each treatment, a total of 80 individuals participated in these modified treatments. The experimental procedures were the same as in our initial Low and High design.

Results from the modified treatments show that the change in incentives, if anything, increases the frequency of $10 contributions. Respectively 10 and 15% of participants contribute $10 in the Modified-Low and Modified-High treatments.[32] Similar to the initial treatments, a large majority of the dominated $10 choices are made by fast decision-makers, accounting for 80% of the $10 contributions (2-sided Fisher exact test $p = 0.087$).

We also find that the modification of payoffs does not alter the above documented comparative statics. Fig. 4 shows the mean contributions by response time in each of the two modified treatments. The mean contributions by fast decision-makers continue to be indistinguishable by treatment (mean Mod-Low = $6.22, mean Mod-High = $6.00, $p = 0.802$), while mean contributions by slow decision-makers differ significantly by treatment (mean Mod-Low = $5.00, mean Mod-High = $6.89, $p = 0.005$). Thus, as in the initial treatments, contributions by fast decision-makers are insensitive to incentives. The rate of mistakes and equilibrium play also replicate our initial results.

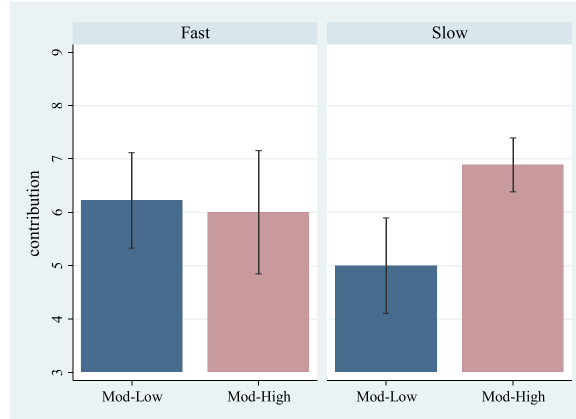

Fig. 4. Mean contribution by fast and slow decision-makers, Mod-Low and Mod-High, Part 1
Note: Fast responses are those made is less than the median response time of the pooled sample of participants (36.5 s). Slow responses are those made in more than the median response time.

Fast decision-makers account for 69.0% of the mistakes observed in the two treatments (2-sided Fisher exact test $p = 0.019$) and for 10.5% of the observed equilibrium contributions (2-sided Fisher exact test $p < 0.001$).[33]

4.4.2. Exogenously imposed time limits: time-pressure and time-delay

To determine the extent to which our comparative statics may be influenced by selection, we explore whether the results are robust to using an exogenously set time limit to secure fast and slow decisions, respectively. For this we conduct two additional sets of treatments. In one set of time-pressure treatments, we force participants to make choices within a given time limit. In another set of time-delay treatments, we allow participants to finalize their decisions only once the time limit has passed. We use the modified payoff structure (Mod-Low and Mod-High) to ensure that $10 contributions are mistakes from the perspective of the individual and of the other group members, and we use the median response time from these endogenous-time modified treatments to establish the time limit (35 s).

Instructions and tutorial procedures were the same as those used in treatments without a time limit. However, after the tutorial and right before the decision screen, participants were presented with an information screen that described the time-limit manipulation. In the time-pressure treatment this screen specified that they would earn $0 and contribute $0 to the group account if they did not make a choice within the time limit.[34] The strong incentive to obey the time limit aimed to incentivize compliance and secured that failure to do so is a mistake from an individual and other-regarding perspective. By design, subjects in the time-delay treatment could not disobey the time limit, and the information screen solely informed participants that while seeing the payoff table and decision screen they would not be able to submit their decision until after the time limit had passed. In both treatments the decision screen showed the payoff table, the timer, and reminded them of the time limit. All other procedures were the same as

[30] In the initial interior equilibria treatments, the marginal cost of contributing $10 rather than $9 is $3.25 in the Low treatment and $1.25 the High treatment. The marginal benefit to others from contributing is $0.75, or $0.25 per group member. Contributions of $10 rather than $9 thus decrease total group payoffs by $2.50 and $0.50 in the Low and High treatments, respectively.

[31] Information about the exact payoff function used to generate payoff tables in these modified treatments is provided in the Appendix. The payoff tables are shown in the online Appendix.

[32] In the initial Low (High) treatment 8 (10) percent contribute $10.

[33] Excluding an outlier, a probit regression of mistakes on response time and treatment provides a marginal effect on response time of -0.0046 (s.e. = 0.002, $p = 0.028$). The outlier is associated with a 346 s response time. In comparison, the next longest decision time in our Mod-Low and Mod-High treatments is 136 s. Including the outlier, the coefficient on response time remains negative but is statistically insignificant (coeff: -0.0008, s.e. = 0.001, $p = 0.464$). See online Appendix D for a scatterplot of contributions and response time. Results mirroring those of Section 4.3 for all robustness treatments are presented in the online Appendix.

[34] Screenshots of the relevant information and decision screens are presented in online Appendix E.

in the treatments without a time limit, including Part 2 where there was no time limit.[35]

Using a between-subject design, a total of 160 undergraduate students participated in the time limit treatments. None of them had participated in any other treatment. Using a 2×2 design, a total of 4 treatments were conducted: (1) Mod-Low with time pressure, (2) Mod-Low with time delay, (3) Mod-High with time pressure, and (4) Mod-High with time delay. We conducted two sessions of each treatment, each with 20 participants.

Out of the 80 participants that made decisions in Part 1 of the time-pressure treatments, 5 failed to decide within the time limit. One in the Mod-Low treatment and 4 in the Mod-High treatment. Because these choices were associated with $0 contributions by design, we include them in the analysis. All results are robust to excluding them.

We replicate our previous results when classifying all participants in the time-pressure treatments as fast decision-makers and all participants in the time-delay treatment as slow decision-makers. Fig. 5 shows the mean contribution in each of the time-limit treatments. Mean contributions by fast decision-makers do not respond to incentives (mean Mod-Low = \$5.85, mean Mod-High = \$5.55, $p = 0.635$),[36] while mean contributions by slow decision-makers do (mean Mod-Low = \$5.43, mean Mod-High = \$7.38, $p = 0.000$).[37] The frequency of mistakes and equilibrium play by fast versus slow decision-makers also mirror those observed in the previously presented experiments. Pooling the time-pressure and time-delay data, we find that fast decision-makers account for 67.8% of the observed mistakes (i.e., contributions below the equilibrium and contributions of $10) and for 35.3% of the observed equilibrium contributions. Two-sided Fisher exact tests reject the null hypothesis that mistakes and equilibrium choices are equally distributed across the time-pressure and time-delay treatments ($p = 0.001$ for mistakes and $p = 0.081$ for equilibrium choices, respectively). Thus, time pressure increases the rate of mistakes relative to the time-delay treatment.[38]

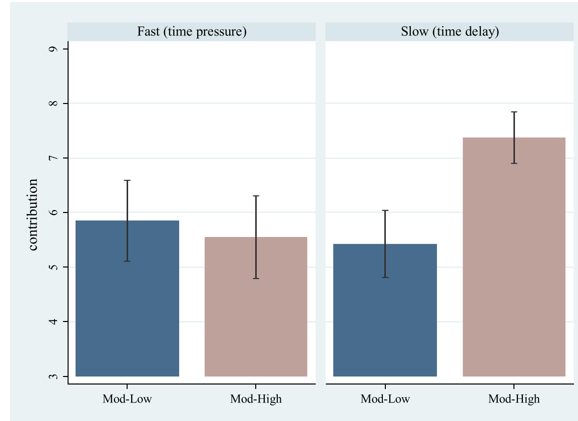

Fig. 5. Mean contribution by exogenous response time and treatment, Part 1.

4.4.3. Results of part 2: dynamics of contributions

Choices made in Part 2 of our experiments further allow us to assess the extent to which choices are reflective of preferences. Recall that Part 2 is a ten-period version of Part 1 with random re-matching of group members in each period and no time limit. We present the data from all public-good games with interior equilibria examined so far in this section because the same Part 1 comparative statics were secured for all the games, and because the response time is endogenously chosen in every session of Part 2. We thus have data for a total of 400 participants.

The left panel of Fig. 6 shows average contributions in all of our Low and High treatments. The right panel pools the data from all treatments with the same dominant strategy equilibrium (i.e., Low or High). Both panels show that with repetition contributions decrease on average in the Low treatments, while they increase on average in the High treatments. That is, contributions converge to the equilibrium prediction from above in the Low treatments and from below in the High treatments. It is noteworthy that by round seven the median contribution corresponds to the equilibrium in both the Low and the High treatments (see right panel of Fig. 6).

The opposing directions of convergence in Part 2 are consistent with the interpretation that overcontribution in the Low treatment and undercontribution in the High treatment can be (partly) attributed to mistakes. Looking at the frequency of equilibrium play and of mistakes supports this interpretation. The share of equilibrium play increases from 27.5% in Part 1 to 67.75% in the last period of Part 2 in the pooled sample of Low and High treatments.[39] Mistakes, on the other hand, decrease from 30.25% in Part 1 to 8.5% in the last period of Part 2. The decrease is sharper in the High treatment, where the set of actions that can be classified as mistakes is larger and mistakes are more common. The rate of mistakes decreases in the Low treatments from 11.5% in Part 1 to 1% in the last period of Part 2, while it decreases in the High treatments from 49% in Part 1 to 16% in the last period of Part 2.[40]

Using Part 1 response time (fast vs. slow) to examine contribution behavior in Part 2 provides an additional way of assessing how contributions change with deliberation and repetition. The contributions by fast decision-makers converge with repetition in Part 2 to the contributions made by slow decision-makers. Convergence again occurs from the middle. Fast decision-makers initially contribute more than slow decision-makers in the Low treatments, while they initially contribute less than slow decision-makers in the High treatments. While convergence from above in the Low treatments may be explained by individuals becoming more selfish and/or by individuals correcting mistakes when given more experience with a decision, convergence from below in the High treatments instead can only be explained by individuals becoming more generous and/or correcting mistakes. The joint results thus lend support to the opposing directions of convergence resulting from a correction of mistakes: fast subjects, who made error-prone decisions in Part 1, learn not to play dominated strategies (see online Appendix Fig. G1).

4.4.4. Summary

The results from the modified treatments, from the time-pressure and time-delay treatments, and from the Part-2 behavior are consistent with our initial interpretation of results from Part 1. Fast decision-

[35] The only additional difference was a $4 survey completion fee that was added as a surprise after all contribution decisions were made in the time-pressure and time-delay treatments. This $4 bonus ensured that the same recruiting message could be used as in the treatments without a time limit.

[36] Excluding the decisions that did not obey the time limit Mean Mod-Low = \$6, Mean Mod-High = \$6.167, $p = 0.771$.

[37] See Appendix Table 1 for a comparison of the design features and results from the different treatments.

[38] As response time is exogenously manipulated it is less clear how we should examine the relationship between the rate of mistakes and time. Pooling the time-pressure and time-delay data and conducting a similar exercise to that presented in previous sections, a probit regression of mistakes on (endogenous) response time and Mod-High treatment provides a significant marginal effect on response time of -0.00843 (s.e. = 0.002, $p = 0.001$).

[39] The share of equilibrium play increases from 24.5 to 61.5% in the Low treatments and from 30.5 to 74% in the High treatments.

[40] Contributions below the dominant strategy are mistakes in all treatments. Contributions of $10 are mistakes in the Mod-Low and Mod-High treatments, but not necessarily in the initial Low and High treatments. The marginal effect of probit regression of mistakes on period and treatment with standard errors clustered at the session level provides a significant marginal effect on period of -0.011 (s.e. = 0.002, $p < 0.001$). By treatments the coefficient is -0.006 (s.e. = 0.001, $p < 0.001$) for Low and -0.018 (s.e. = 0.003, $p < 0.001$) for High. Score bootstrapped tests that correct for the small number of clusters provide similar results.

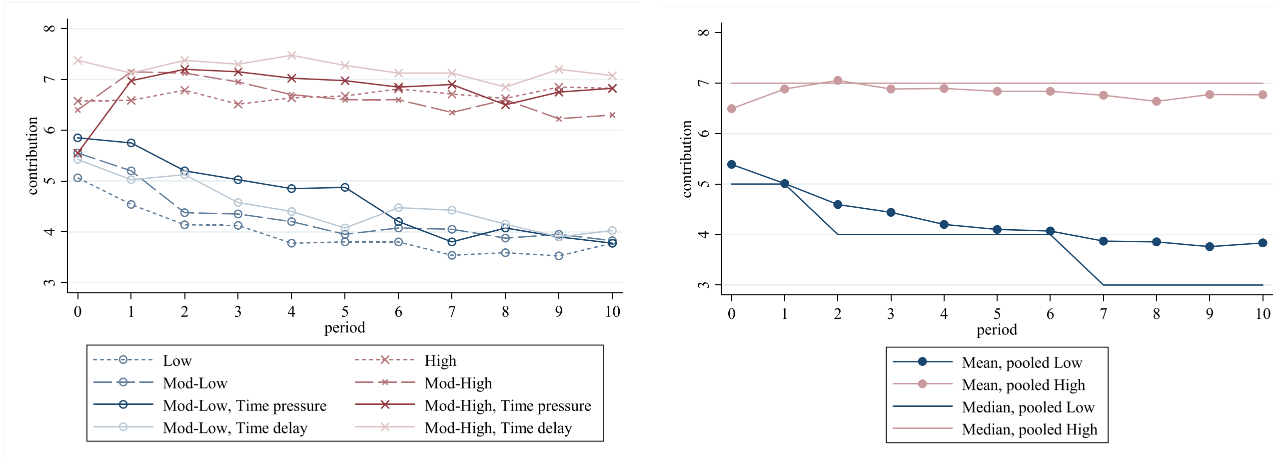

Fig. 6. Contribution by round and treatment
Note: Period 0 denotes Part 1.

makers appear to be less sensitive to individual and group incentives and to be more prone to making mistakes. Depending on the strategic environment, these characteristics make fast decision-makers appear more generous in some circumstances and less generous in others. We find in each of three types of treatments that mean contributions by fast decision-makers exceed those by slow decision-makers in the Low treatments, while the reverse holds in each of the High treatments. This calls for caution when interpreting fast decisions as being reflective of generosity or, more generally, preferences over payoffs. Rather, our results indicate that the previously documented greater contributions by fast decision-makers likely result from fast decision-makers being more prone to making mistakes.

5. Public-good games with equilibria at the boundary (VCM)

To disentangle mistakes from generosity, we implemented public-good games with an interior equilibrium. These games differ from that of the standard VCM. The interior equilibrium public-good game may be more confusing and potentially result in higher rates of error, and our reliance on payoff tables may have triggered a cognitive mind state without regard for others (e.g., Charness et al., 2004). While these differences are unlikely to affect our comparative statics we, nonetheless, examine sensitivity to the location of the equilibrium in a less complex set of environments.

In a set of VCM treatments, we keep the return to contributing constant (as in the standard VCM), which implies that the dominant strategy equilibrium is on the boundary of the strategy set. We examine two such VCM environments where we modify the return to the individual from contributing: one where the dominant strategy equilibrium, as in the standard VCM, is zero provision (Low-VCM) and one where the dominant strategy equilibrium is full provision (High-VCM). In these treatments, members of four-person groups can contribute none, part, or all of an \$8 endowment to a group account, where every contributed dollar is doubled and split equally between group members.[41] Hence, across treatments we keep constant the marginal benefit to others from contributing. This marginal per capita return (MPCR) is \$0.50, and the equilibrium contribution is zero in the Low-VCM treatment. For the High-VCM we secure an equilibrium with full provision by adding to the \$0.50 MPCR an individual contribution bonus of \$0.60 per dollar contributed. Only the individual contributing receives the contribution bonus. As in the standard VCM, instructions are simple and payoffs are characterized without the use of a payoff table and the associated tutorial. The rest of the procedures are as in our previous experiments.

We conducted four sessions of the VCM treatments, two sessions of the Low-VCM treatment and two sessions of the High-VCM. In total 40 individuals participated in the Low-VCM and 36 participated in the High-VCM treatment. Fig. 7 shows the distribution of contributions by treatment. We first ignore the dominant strategies of \$0 in the Low-VCM and \$8 in the High-VCM and examine non-equilibrium contributions in the range of \$1 through \$7. Contributions in this range are welfare improving in the Low-VCM but are dominated from a group perspective in the High-VCM. Despite these very different payoff consequences, the contribution distributions are very similar (Kolmogorov-Smirnov $p = 0.814$). Equally striking is the similarities in the frequency of \$0 and \$8 contributions. In what follows we look at how choices by fast and slow decision-makers influence the similarities in contribution distributions across treatments.

Using the median response time of 35.5 s in the pooled sample of VCM treatments to distinguish between fast and slow decision-makers, we find that the high frequency of non-equilibrium play is largely due to fast decision-makers.[42] Also mistakes, which can only be identified in the High-VCM treatment, are associated with fast response times. With 70% of dominated choices in the High-VCM being made by fast decision-makers, we reject that mistakes are equally likely for fast and slow decision-makers (2-sided Fisher's exact test $p = 0.019$).[43] Interestingly, contributions of 0 in the High-VCM are primarily made by fast decision-makers. Equilibrium and full provision choices, on the other hand, are associated with slow response times in both treatments (2-sided Fisher's exact test $p = 0.097$ for the pooled sample for each of these two provision choices). Choices in the middle of the strategy set (i.e., providing half of the endowment), which are welfare improving relative to the dominant strategy in the Low-VCM but are dominated from an individual and other-regarding perspective in the High-VCM, are also

[41] To secure payoff ranges similar to the ones in our other experiments, we provide each participant with an \$8 endowment. This secures that maximum group payoffs across treatments are comparable to those in the interior equilibrium treatments. See online Appendix A and B for instructions and payoff information. Payoff descriptions were provided to subjects on the same screen used to make contribution decisions. Response time was measured from the moment the decision screen was shown.

[42] There are no statistically significant differences in response time by treatment (Kolmogorov-Smirnov $p = 0.279$; Wilcoxon Mann-Whitney rank-sum test $p = 0.254$). The cumulative distribution functions of response time by VCM treatment are presented in online Appendix Figure H1.

[43] Excluding an outlier, a probit regression of mistakes on response time provides a significant marginal effect on response time of -0.0111 (s.e. = 0.004, $p = 0.004$). The outlier is associated with a 277 s response time. The next slowest response time in these treatments has a response time of 103 s. Including the outlier the marginal effect continues to be negative but statistically insignificant (coeff: -0.0011, s.e. = 0.002, $p = 0.468$).

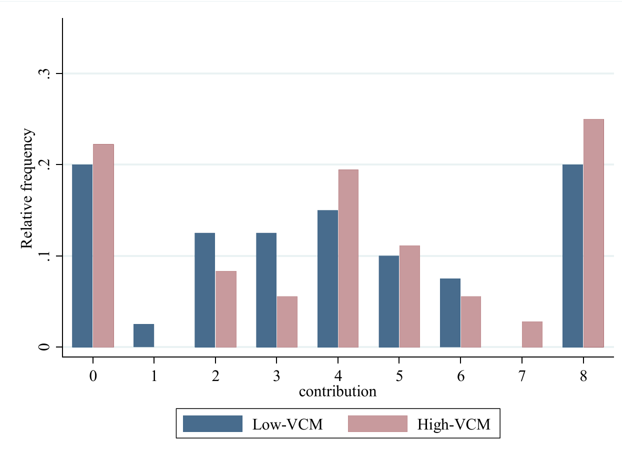

Fig. 7. Histogram of contributions by treatment, Part 1 VCM treatments
Note: The equilibrium contribution is 0 in the Low treatment and 8 in the High treatment. The group-payoff-maximizing contribution is 8 in both treatments.

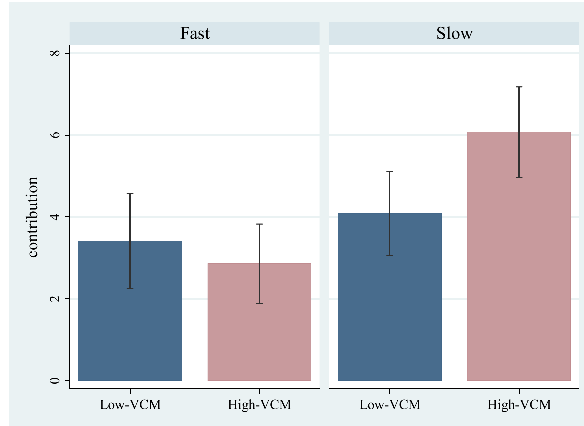

Fig. 8. Mean contribution by fast and slow decision-makers, Part 1 VCM treatments.

more frequently selected by fast decision-makers.[44]

Fig. 8 shows for fast and slow decision-makers the mean contributions by treatment. For the High-VCM we replicate the results from the interior High treatments: fast decision-makers contribute less than slow decision-makers (\$2.86 vs. \$6.07, $p < 0.01$). In the Low-VCM we do not, however, replicate the finding that fast decision-makers contribute more than slow decision-makers (\$3.41 vs. \$4.09, $p = 0.457$).[45] While inconsistent with the interpretation that fast decision-makers are more generous, this result need not be inconsistent with fast decisions being more prone to error. Indeed, the reason for looking at environments with an interior equilibrium was precisely that in the Low-VCM all equilibrium deviations are welfare improving, thus making it impossible to separate mistakes from generosity. Consistent with fast decisions being more prone to error, fast decisions appear insensitive to treatment while slow decisions vary significantly by treatment.[46]

The results from these simple VCM games mirror the results for our interior public-good games. Fast decision-makers are less sensitive to incentives and more prone to making mistakes.[47]

6. Conclusion

Response times are increasingly used to draw inference on individual preferences. We argue that such inference can be misleading when mistakes are correlated with response time. To demonstrate this, we revisit the finding that individuals who make (or have to make) fast decisions give more in the standard VCM. While this finding has been seen as evidence that individuals are intuitively generous, we argue that large fast contributions may instead result from individuals making mistakes.

As mistakes cannot be identified with the standard VCM, we examine contributions in public-good games with unique interior equilibria in dominant strategies. In these games, we show that the comparative statics of fast and slow decision-makers reverses with the location of the equilibrium. Fast decision-makers tend to be more generous than slow decision-makers when the equilibrium is located below the midpoint of the strategy set, and less generous when the equilibrium is located above the midpoint. Even though incentives change with the location of the equilibrium, we find that mean contributions for fast decision-makers do not vary.

In our study, we use public-good games where a subset of the strategy set is dominated from an individual and other-regarding perspective. That is, where there are deviations from equilibrium that simultaneously decrease the earnings of the decision-maker and of all other group members. Classifying these deviations as mistakes, we show that the rate of mistakes decreases with response time. Even though the set of actions that constitute mistakes increases as we move the equilibrium from below to above the midpoint of the strategy set, fast decision-makers make choices that are indistinguishable across treatments. These results hold both when response time is endogenously chosen and when it is exogenously imposed by the experimenter.

The observed pattern of behavior suggests that fast responses rather than being indicative of intuitive generosity instead result from fast mistakes.[48] Mistakes may result from fast decision-makers being confused, not paying attention, or lacking motivation. In evaluating our ability to draw inference on preference from response time, it is only necessary to show that mistakes occur and that the rate of mistakes varies with response time. Independent of the source, it is evident that mistakes are an important confound.

Our finding that mistakes confound the inference on preferences from response times suggests that caution is warranted when considering other experimental manipulations that also interact with mistakes. For example, giving participants an option to (continuously or repeatedly) revise an initial decision to determine whether fast decisions are impulsive will not only result in corrections for those who in the heat of the moment contributed, but also for those who made a mistake and wish to correct their decision. Just as response times are correlated with error, experimental manipulations that influence error will make inference on preferences difficult.[49]

The results of our paper extend beyond the study of response times

[44] These results mirror Rubinstein (2016), who finds that full contribution is associated with the largest response times in a 5 person Low-VCM, followed by zero and high contribution choices of 60–90% of the endowment. Contributions equal to the midpoint of the strategy set are associated with the smallest response times.

[45] This result is consistent with Bouwmeester et al. (2017), who also fail to replicate the comparative statics in the VCMs by Rand et al. (2012)

[46] Mean contributions by treatment are not distinguishable for fast decision-makers (Mean Low = \$3.41, Mean High = \$2.86, $p = 0.53$), while they are distinguishable for slow decision-makers (Mean Low = \$4.09, Mean High = \$6.07, $p = 0.03$).

[47] Part 2 reveals convergence to equilibrium in the Low-VCM treatment but not in the High-VCM treatment. The frequency of equilibrium play increases in the Low-VCM from 20% in Part 1 to 70% in the last period of Part 2, while in the High-VCM it is at 25% in Part 1 and in the last period of Part 2. Failure to converge in the High-VCM may result from out-of-equilibrium relative earnings being lower for those who contribute the equilibrium amount. For example a contribution profile of $(g_1,g_2,g_3,g_4) = (8,0,0,0)$ secures earnings of (8.8, 16.8, 16.8, 16.8). Thus, non-equilibrium play may be reinforced.

[48] Error may play a smaller role in simple settings and a larger role in more complex ones. This may explain why in the simple dictator game and in donation experiments a positive correlation has been documented between kindness and response times (Piovesan and Wengström, 2009; Fiedler et al., 2013; Lohse et al., 2016), while a negative correlation has been found in the standard VCM (Rand et al., 2012; Lotito et al., 2013; Nielsen et al., 2014) and in the ultimatum game (Branas-Garza et al., 2016).

[49] For example, mistakes may increase as cognitive loads are increased and similarly make it difficult to infer underlying preferences.

and intuitive choices in public-good games and social dilemmas. They indicate that independent of the environment caution is warranted when trying to draw inferences about preferences from response times. While we found fast decision-makers to be insensitive to the payoffs associated with their choices, slow decision-makers were instead very sensitive to changes in payoffs. Our results thus suggest that, compared to fast decision-makers, the choices made by slow decision-makers better reflect individual preferences over payoffs.

The concern for error raised here is likely to be greater when examining one-shot interactions. Response times may better reflect preferences in environments, such as those recently used to study drift diffusion models, where individuals are presented with choices between familiar products and asked to repeatedly make decisions in comparable environments. Our study also suggests that theoretical models of decision-making may need to consider not only the possibility of dual processes and response times but also how errors relate to response times (see e.g., Caplin and Martin, 2016). Only with such models at hand will empirical researchers be able to use response times for unbiased inference on individual preferences.

In addition to examining whether preferences can be inferred from response time, our paper makes three broader methodological contributions. First, the finding that some participants seem insensitive to incentives provides evidence of the role of error, and the broader need to evaluate the effect that such behavior can have on inference. Reminiscent of the "failure of game form recognition," found by Cason and Plott (2014) this payoff-insensitivity suggests that some participants engage in a decision environment that is very different from that intended by the researcher. Second, our study points to response time as a potential control for error. As a robustness check, it may be of interest to evaluate separately decisions that occur with some minimal time delay. While response time is a crude measure of mistakes, it is at least a starting point for reducing the potential role of error. Finally, our results serve as a general caution for our response to novel comparative statics. Identification requires not only an empirical confirmation of a predicted comparative static, but also elimination of alternative explanations of the relationship. Failure to eliminate error as an alternative explanation for the difference between fast and slow decisions demonstrates the importance of eliminating confounds and securing that our studies are internally valid.

Appendix A Payoffs

We follow Bracha et al. (2011) and use a piecewise linear payoff structure to construct public-good games with interior equilibria in dominant strategies. Payoffs in the Low and High treatments are constructed using the following function:

$$\pi_i(g_i, G_{-i}) = \begin{cases} 10 + \alpha g_i + \sigma G_{-i} & \text{if } \; 0 \le g_i \le g^L \\ 10 + \alpha g^L + \beta(g_i - g^L) + \sigma G_{-i} & \text{if } g^L < g_i \le g^H \\ 10 + \alpha g^L + \beta(g^H - g^L) + \gamma(g_i - g^H) + \sigma G_{-i} & \text{if } g^H < g_i \le g^P \\ 10 + \alpha g^L + \beta(g^H - g^L) + \gamma(g^P - g^H) + \delta(g_i - g^P) + \sigma G_{-i} & \text{if } g^P < g_i \le 10 \end{cases} \tag{1}$$

where π_i denotes the monetary payoff individual i receives from his or her contribution g_i to the group account and the sum of contributions G_{-i} made by the three other group members. σ is the constant return from the contribution by others, while the threshold g^L, $g^H$and g^P along with the parameters α, β, γ, and δ secure the piece-wise linear approximation of the concave private benefit from giving. Threshold contributions g^L and g^H denote respectively the individual equilibrium contribution in the Low and High treatments, and g^P denotes the individual contribution associated with the unique group-payoff-maximizing outcome. Parameter σ remains constant across the Low and High treatments, while α, β, γ, and δ vary. That is, across treatments we hold constant the benefit each group member gets from the contribution by others (σ), while the individual's private return from contributing is varied.

Table A1
Payoff function parameters by treatment.

Parameter	Low	High
α	1.450	0.116
β	-0.250	0.250
γ	-0.500	-0.500
δ	-3.250	-1.250
σ	0.250	0.250
g^L	3.000	3.000
g^H	7.000	7.000
g^P	9.000	9.000

Modified interior public-good games presented in Section 4.4 change some parameters of this payoff function to ensure that $10 contribution choices are mistakes from an individual and other-regarding perspective. Specifically, δ is set to −2.25 and −0.25 in the Modified-Low and High treatments, respectively, while σ = −0.15 in both treatments when $g_i > 9$.

Payoff functions were not presented to participants in any treatment. Treatments with interior equilibria only provided subjects with the payoff tables. We provide the payoff tables used in the Low and High treatments in this Appendix. The payoff tables used in the other treatments with interior equilibria are provided in the online Appendix, together with the instructions, and payoff descriptions used in the public-good games with equilibria at the boundary.

Table A2
Payoff table Low treatment.

Average investment made by the other group members

Your Investment	0	1	2	3	4	5	6	7	8	9	10
0	10.00 / 10.00	10.75 / 11.95	11.50 / 13.90	12.25 / 15.85	13.00 / 16.10	13.75 / 16.35	14.50 / 16.60	15.25 / 16.85	16.00 / 16.85	16.75 / 16.85	17.50 / 14.10
1	11.45 / 10.25	12.20 / 12.20	12.95 / 14.15	13.70 / 16.10	14.45 / 16.35	15.20 / 16.60	15.95 / 16.85	16.70 / 17.10	17.45 / 17.10	18.20 / 17.10	18.95 / 14.35
2	12.90 / 10.50	13.65 / 12.45	14.40 / 14.40	15.15 / 16.35	15.90 / 16.60	16.65 / 16.85	17.40 / 17.10	18.15 / 17.35	18.90 / 17.35	19.65 / 17.35	20.40 / 14.60
3	14.35 / 10.75	15.10 / 12.70	15.85 / 14.65	16.60 / 16.60	17.35 / 16.85	18.10 / 17.10	18.85 / 17.35	19.60 / 17.60	20.35 / 17.60	21.10 / 17.60	21.85 / 14.85
4	14.10 / 11.00	14.85 / 12.95	15.60 / 14.90	16.35 / 16.85	17.10 / 17.10	17.85 / 17.35	18.60 / 17.60	19.35 / 17.85	20.10 / 17.85	20.85 / 17.85	21.60 / 15.10
5	13.85 / 11.25	14.60 / 13.20	15.35 / 15.15	16.10 / 17.10	16.85 / 17.35	17.60 / 17.60	18.35 / 17.85	19.10 / 18.10	19.85 / 18.10	20.60 / 18.10	21.35 / 15.35
6	13.60 / 11.50	14.35 / 13.45	15.10 / 15.40	15.85 / 17.35	16.60 / 17.60	17.35 / 17.85	18.10 / 18.10	18.85 / 18.35	19.60 / 18.35	20.35 / 18.35	21.10 / 15.60
7	13.35 / 11.75	14.10 / 13.70	14.85 / 15.65	15.60 / 17.60	16.35 / 17.85	17.10 / 18.10	17.85 / 18.35	18.60 / 18.60	19.35 / 18.60	20.10 / 18.60	20.85 / 15.85
8	12.85 / 12.00	13.60 / 13.95	14.35 / 15.90	15.10 / 17.85	15.85 / 18.10	16.60 / 18.35	17.35 / 18.60	18.10 / 18.85	18.85 / 18.85	19.60 / 18.85	20.35 / 16.10
9	12.35 / 12.25	13.10 / 14.20	13.85 / 16.15	14.60 / 18.10	15.35 / 18.35	16.10 / 18.60	16.85 / 18.85	17.60 / 19.10	18.35 / 19.10	19.10 / 19.10	19.85 / 16.35
10	9.10 / 12.50	9.85 / 14.45	10.60 / 16.40	11.35 / 18.35	12.10 / 18.60	12.85 / 18.85	13.60 / 19.10	14.35 / 19.35	15.10 / 19.35	15.85 / 19.35	16.60 / 16.60

The BLUE number on the left is your payoff, the BLACK number on the right is the payoff of each of the other group members when they each invest the amount listed.

Mistake   Dominant strategy   Group-payoff-maximizing contribution

Table A3
Payoff table High treatment.

Average investment made by the other group members

Your Investment	0	1	2	3	4	5	6	7	8	9	10
0	10.00 / 10.00	10.75 / 10.62	11.50 / 11.23	12.25 / 11.85	13.00 / 12.60	13.75 / 13.35	14.50 / 14.10	15.25 / 14.85	16.00 / 14.85	16.75 / 14.85	17.50 / 14.10
1	10.12 / 10.25	10.87 / 10.87	11.62 / 11.48	12.37 / 12.10	13.12 / 12.85	13.87 / 13.60	14.62 / 14.35	15.37 / 15.10	16.12 / 15.10	16.87 / 15.10	17.62 / 14.35
2	10.23 / 10.50	10.98 / 11.12	11.73 / 11.73	12.48 / 12.35	13.23 / 13.10	13.98 / 13.85	14.73 / 14.60	15.48 / 15.35	16.23 / 15.35	16.98 / 15.35	17.73 / 14.60
3	10.35 / 10.75	11.10 / 11.37	11.85 / 11.98	12.60 / 12.60	13.35 / 13.35	14.10 / 14.10	14.85 / 14.85	15.60 / 15.60	16.35 / 15.60	17.10 / 15.60	17.85 / 14.85
4	10.60 / 11.00	11.35 / 11.62	12.10 / 12.23	12.85 / 12.85	13.60 / 13.60	14.35 / 14.35	15.10 / 15.10	15.85 / 15.85	16.60 / 15.85	17.35 / 15.85	18.10 / 15.10
5	10.85 / 11.25	11.60 / 11.87	12.35 / 12.48	13.10 / 13.10	13.85 / 13.85	14.60 / 14.60	15.35 / 15.35	16.10 / 16.10	16.85 / 16.10	17.60 / 16.10	18.35 / 15.35
6	11.10 / 11.50	11.85 / 12.12	12.60 / 12.73	13.35 / 13.35	14.10 / 14.10	14.85 / 14.85	15.60 / 15.60	16.35 / 16.35	17.10 / 16.35	17.85 / 16.35	18.60 / 15.60
7	11.35 / 11.75	12.10 / 12.37	12.85 / 12.98	13.60 / 13.60	14.35 / 14.35	15.10 / 15.10	15.85 / 15.85	16.60 / 16.60	17.35 / 16.60	18.10 / 16.60	18.85 / 15.85
8	10.85 / 12.00	11.60 / 12.62	12.35 / 13.23	13.10 / 13.85	13.85 / 14.60	14.60 / 15.35	15.35 / 16.10	16.10 / 16.85	16.85 / 16.85	17.60 / 16.85	18.35 / 16.10
9	10.35 / 12.25	11.10 / 12.87	11.85 / 13.48	12.60 / 14.10	13.35 / 14.85	14.10 / 15.60	14.85 / 16.35	15.60 / 17.10	16.35 / 17.10	17.10 / 17.10	17.85 / 16.35
10	9.10 / 12.50	9.85 / 13.12	10.60 / 13.73	11.35 / 14.35	12.10 / 15.10	12.85 / 15.85	13.60 / 16.60	14.35 / 17.35	15.10 / 17.35	15.85 / 17.35	16.60 / 16.60

The BLUE number on the left is your payoff. The BLACK number on the right is the payoff of each of the other group members when they each invest the amount listed.

Mistake Dominant strategy Group-payoff-maximizing contribution

Table A4
Summary of design features and results: part 1, all treatments.

	Public-good games with interior equilibria						Public-good games with Equilibria at the boundary	
	Original payoffs		Modified payoffs		Time limit			
	Low	High	Mod-low	Mod-high	Mod-low	Mod-high	Low-VCM	High-VCM
Design features								
Endowment	10	10	10	10	10	10	8	8
Dominant strategy	3	7	3	7	3	7	0	8
Group-payoff-max. contribution	9	9	9	9	9	9	8	8
Mistakes	0–2	0–6	0–2, 10	0–6, 10	0–2, 10	0–6, 10	n.a.	0–7
Fast decision-makers								
Mean contribution	5.537	6.077	6.222	6.000	5.850	5.550	3.412	2.857
(std. error)	(0.425)	(0.440)	(0.515)	(0.671)	(0.439)	(0.450)	(0.665)	(0.562)
N obs.	41	39	18	22	40	40	17	21

Slow decision-makers								
Mean contribution	4.564	7.049	5.000	6.889	5.425	7.375	4.087	6.067
(std. error)	(0.316)	(0.188)	(0.518)	(0.290)	(0.367)	(0.281)	(0.596)	(0.628)
N obs.	39	41	22	18	40	40	23	15
All decision-makers								
Mean contribution	5.063	6.575	5.550	6.400	5.637	6.463	3.800	4.194
(std. error)	(0.271)	(0.240)	(0.375)	(0.394)	(0.285)	(0.283)	(0.442)	(0.493)
N obs.	80	80	40	40	80	80	40	36
Two-sided *t*-test (*p*-values)								
Fast vs. slow (within treatment)	0.072	0.042	0.106	0.267	0.460	0.001	0.457	0.001
Low vs. High: Fast decision-makers	0.380		0.801		0.635		0.525	
Low vs. High: Slow decision-makers	0.000		0.005		0.000		0.034	
Low vs. High: All decision-makers	0.000		0.122		0.042		0.552	

Note: We employed a between-subject design and have data for a total of 476 participants across all treatments.

Appendix B Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jpubeco.2018.02.010.

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